Residential Façade Optimisation for Daylight-Thermal Balance and Climate Change Impact in a Hot and Humid Climate

[1]Institution 1, City 1, Country 1
[2]Institution 2, City 2, Country 2

Abstract

Designing for daylighting-thermal balance for a hot and humid climate should be properly considered due to the contradictory relationship between thermal energy and daylighting. Often the occupant of residential houses in such climate chooses to install large overhangs to reduce solar heat gain into the house. However, this practice can cause overshading phenomenon which leads to insufficient natural daylight in the interior. This study employed global sensitivity analysis and multi-objective optimisation (MOO) to find an optimal solution that reaches a trade-off between daylighting and thermal energy performance in hot and humid climates. The methods were applied to a double-storey terrace housing archetype and changes in optimal solutions were also studied for the future climate. The sensitivity analysis identified glazing transmittance (GT) as the most significant parameter for daylighting while the room depth (RD) parameter is significant for thermal energy performance. The selected solutions for this study observed an increase in daylight performance by 10.2% to 13.4%, depending on the climate scenarios. On the other hand, the thermal energy performance of the selected solutions showed a trade-off between daylight and thermal energy performance.

Highlights

- The optimisation process is critical for finding a long-term and robust solution against climate change.
- The internal light shelf is more sensitive to daylight performance while the external light shelf is more sensitive to thermal-related performance.
- The multi-objective optimisation succeeds to find a trade-off solution for contradictory objective functions like daylight and thermal performance.

Introduction

Dwelling in a tropical climate must be designed to effectively mitigate the high intensity of solar heat gain throughout the year. One viable option for this problem is by using external shading devices which are effective in limiting excessive solar heat gain into the interior. Shading devices such as large external overhang is a popular design option for homeowners in the tropical climate of Malaysia. Specifically for terraced housing, the overhang is installed at the front façade of the house which also covers the external porch area. The large overhang design is also desirable by Malaysian homeowners because Malaysia is subject to heavy rainfall throughout the year. Hence, having an overhang that covers most of the porch area becomes an important design factor in such dwellings, and it is always included in new development (Nik Ramzi Shah & Mohd. Rasdi, 2017).

However, the overhang does not simply limit solar gains and protects the porch area from heavy rainfall, they also reduce the amount of daylighting in the building if it is not properly designed (Yu et al., 2020). The problem is heightened especially for the intermediate unit which typically has only two façades for fenestration, located at the front and the back of the house. The typical layout of terrace housing in Malaysia has a deep and narrow floor plan where the width of the house is usually around 6m to 8m with a depth of 10m to 13m (Nik Ramzi Shah & Mohd. Rasdi, 2017). These design attributes limit the daylight from entering deep into the space, resulting in additional usage of artificial lighting during the day. Our preliminary study on the daylight level of such houses in Malaysia suggests that the current daylight performance of the house is below the recommended level of the Energy Efficiency and Use of Renewable Energy for Residential Buildings - Malaysian Standard Code of Practice: MS 2680:2017 (Department of Standards Malaysia, 2017). Thus, this study aims to explore design options that could reach an acceptable trade-off between daylighting and solar heat gain in a hot and humid climate.

When dealing with various design parameters with conflicting objectives, the use of the simulation-based multi-objective optimization (MOO) method was found to be useful. Compared to single-objective optimisation, MOO produces a range of possible solutions that are subject to equivalent importance (Pareto front) rather than producing a single optimal solution. A recent review by Yu et al. (2020) reviewed five methods for studying thermal-daylighting balance and MOO was recommended as the effective method to find a trade-off solution to these objectives. A study by Bahdad et.al (2021) used MOO to investigate the impact of light shelf parameters on visual comfort and thermal energy performance in an office building. The objectives of the study are to increase useful daylight illuminance (UDI), reduce the daylight glare probability (DGP) for better daylight performance, and minimise thermal energy use intensity (EUI). Zani et. Al. (2017) employed the MOO approach for finding the optimal design of innovative concrete shading. The metrics studied in the study were daylight autonomy (DA), UDI and total cooling, heating, and lighting energy demand. Also, Shahbazi et. al. (2019) used the Octopus plugin for Grasshopper, a genetic algorithm MOO tool to investigate an optimised window system. The optimal objectives were UDI and EUI.

The MOO method however is computationally expensive, especially when involving daylight simulation which is known as a time-consuming and laborious process. Moreover, a building system includes a wide range of parameters ranging from building design to the building operation system and often the relationship is highly non-linear. According to a recent review of sensitivity analysis, the method is widely employed by building simulation researchers to combat these challenges (Pang et al., 2020). Sensitivity analysis can establish the input-output relationships of a complex model and determine the significant and neglectable parameters (Andrea et al., 2008). Finding the most influential input parameters enable the size of the search space in the optimisation process to be reduced to design parameters that are critical to the model only. Sensitivity analysis methods are categorized into two approaches, local and global sensitivity analysis. According to Pang et. al. (2020), the local approach is computationally efficient, but it is not suitable for non-linear and/or non-monotonic input parameters. For the non-linear and non-monotonic model, the global sensitivity analysis is necessary to achieve a robust result (Pang et al., 2020).

Method

In this section, an overview of the method used to conduct sensitivity analysis and multi-objective optimisation is provided. There were 4 major steps employed in this study. Firstly, parametric modelling, decision parameters formulation and simulation setup. Decision parameters were created among design strategies that are critical during the early design stage such as the room geometry, orientation, and façade design. Secondly, the parametric model was calibrated against measured data from the literature. In the third step, global sensitivity analysis was performed to determine the most influential input parameters. To find the optimal solution for balancing daylight-thermal performance, the simulation-based multi-objective method was conducted as the last step in this study. A case study is used to prove the pertinence of the proposed methodology. The next section will discuss these methods in detail.

The case study and parametric modelling

The building typology selected for the study is an urban residential building, which is a double-storey terraced housing. This study will be focusing the most problematic area of the house which is the open-plan living and dining area located at the front of the ground floor area. The simulations were performed for the capital city of Malaysia, Kuala Lumpur (3°7'N 101°33'E) which has a tropical wet climate with no dry or cold season. The location is constantly moist and has year-round rainfall according to the Köppen-Geiger climate classification. In the pre-processing stage, a parametric simulation model was created using Rhinoceros 7 and Grasshopper plugin. 11 different design parameters such as room orientation (RO), room width (RW), room depth (RD), room height (RH), shade depth (SD), glazing ratio (GR), glazing transmittance (GT), depth of external and internal light shelf (ELSD & ILSD) and tilt angle of the external and internal light shelf (ELSA & ILSA) were modelled parametrically. All parameters were a continuous type of data.

The research approach in this paper was based on a cross-comparison of simulation results to the base case. The base case was assumed to be two extremes (shaded and unshaded). The base cases had a dimension of 6.0m x 7.0m x 3.0m for the width, depth, and height respectively. There was no light shelf installed for the base case but one of the base cases had a shade of 6.0m width, 4.5m depth and 3.0m height. The thickness of the glazing is 6 mm with a transmittance of 0.6 and a glazing ratio of 30%. The base case was facing south which in this case is 0°. A 1.1m width by 1.9m height door was also modelled to the front façade. The function of the door was to mimic the actual wall-to-window ratio available to the room in actual cases and it constitutes around 10 per cent of the façade area. According to our preliminary calibration study, the shading of the adjacent unit, the partition wall separating these units and the exterior porch floor had a significant impact towards the daylight performance of the room. Hence, to replicate the actual behaviour of the case study, these design elements were also included in the simulated model (Figure 1).

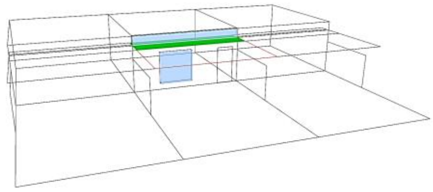


Figure 1: The 3d model of the studied room for the optimisation process.

Simulation setup

The effect of changing the design parameters on daylighting performance was measured using the Ladybug Tool version 1.5.0, a Grasshopper plugin that uses Radiance for annual simulation and illuminance computation. Daylight performance was evaluated using Useful Daylight Illuminance (UDI) which corresponds to MS 2680:2017. UDI is a dynamic daylight performance that defines the annual occurrences of illuminance across the work plane (Nabil & Mardaljevic, 2005). This metric values daylight in a space based on three illumination ranges which are UDIa (acceptable), UDIs (supplementary) and UDIe (excessive). According to MS2680:2017, the recommended illuminance level for a living room and dining room is 200 lux and 250 lux respectively. Thus, the UDIs, UDIa and UDIe bins assigned for the study were <100 lux, 100-2000 lux and >2000 lux respectively. Another daylight metric evaluated in this paper is uniformity ratio (UR). The uniformity ratio is the ratio of the minimum daylight level to the average daylight level in a space. UR evaluates the quality of the illuminance distribution in space. A space with a higher ratio will give the occupant a more comfortable environment where different lighting levels are unnoticeable, hence less artificial lighting will be used during the day. In this study, UR is used to evaluate the performance of the light shelf to redirect daylighting deep into the floor plane.

The set grid of sensor points has a spacing of 0.5m by 0.5m, a height of 0.75m and a boundary of 0.5m from the room walls. The optimal Radiance ambient parameters for the study have been investigated and assigned as reported in Table 1. The values written in brackets are the default parameters that rcontrib adopted. To explore the impact of artificial lighting during the day, the lighting schedule was set from sunrise to sunset which was 07:00 to 19:00. For the occupancy schedule, during weekdays, the room was assumed to be occupied for about 2 hours in the morning and another 6 hours in the late afternoon and evening during the weekdays. While on the weekend, the room was assumed to be occupied from 07:00 to 22:00. There were 22 days of public holiday recorded in the year 2022 for Malaysia and during these days, the room was assumed to be unoccupied because the occupant often went out during the holidays. The reflectance value of the light shelf, wall, roof ceiling and floor are 0.9, 0.75, 0.8 and 0.2 respectively.

Table 1: Radiance ambient parameters for daylight simulation

-ab	-ad	-as	-c	-dr	-dp	-lr	-lw
6	70000	(4096)	(1)	(3)	(512)	(8)	(4e-07)

For energy simulation, OpenStudio 4.5 was used as the energy simulation engine. The annual energy use per floor area (EUI – kWh/m2) was used to compare the efficiency of each design parameter. There were 3 energy metrics investigated in the study which were the annual lighting EUI (LTE), the annual cooling EUI (CLE) and the annual solar Gain EUI (SGE). All surfaces of the room are assumed to be adiabatic except the front façade. The detailed thermal properties and construction of the room are described in Table 2. The lighting load and the occupancy load schedules were identical to those used in the daylight simulation. During occupied hours, it was assumed that 5 people are present. The space was fully air-conditioned, and the HVAC set points for cooling were set at 24^0C. For a hot climate, the heating system is rarely installed in a residential building. Thus, to avoid any heating being calculated in the simulation, the heating set point was set much lower than the standard which was 8^0C. Lastly, the equipment load was assumed to be $41W/m^2$.

Model Calibration

In the present study, the energy results from OpenStudio and the performance of the studied house were verified against the experimental data of Mohamed et. al. (2017). The equipment loads and occupancy hours were selected according to the experimental study. According to Mohamed et. al. (2017), the average monthly energy consumption of a double-storey terrace house is 920 kWh. 14 model variations were tested in the model calibration process and the percentage difference of the last variation achieved an agreement of less than 10% with the experimental data. Hence, the last variation model was used as the model to analyse the daylight and energy performance of the studied room.

Present and Future Climate

To better comprehend the impact of solar heat gain caused by global climate change in the tropical climate, future hourly weather data of the studied location was also analysed in the study. The International Weather for Energy Calculation (IWEC) year for the Kuala Lumpur weather station (486470) was used as the base or present climate in the study. The hourly future climate of Kuala Lumpur was generated using a 'Climate Change World Weather Generator' tool (CCWorldWeatherGen) developed at the University of Southampton (Jentsch et al., 2013). The tool uses a morphing technique to morph a typical meteorological year (TMY) into new future weather files for the year the 2020s, 2050s and 2080s.

CCWorldWeatherGen morphed the baseline data using the HadCM3 global circulation model used in assessment reports by the IPCC. The IPCC's Special Report on Emissions Scenarios (SRES) outline six climate change scenario families namely A1F1, A1B, A1T, A2, B1, and B2. The morphed tool used the A2 climate change scenario by default which was the assumption used for this study. Figure 2 illustrates the probability density function of changes in temperature and relative humidity

Table 2: The thermal properties and construction of the studied room

Building elements	Construction		Thickness (m)	Conductivity W/(m.K)	Density kg/m^3	Spec. heat J/(kg.K)
External wall	227mm brick wall	Cement sand plaster (each side)	0.006	0.533	1800	1000
		Red clay brick	0.215	0.3	1900	840
Internal wall	150mm brick wall	Cement sand plaster (each side)	0.006	0.533	1800	1000
		Red clay brick	0.140	0.3	1900	840
Internal Floor	Concrete floor with tiles	Reinforced concrete floor	0.1	2.3	2300	1000
		Concrete screed	0.05	1.35	2000	1000
		Ceramic tiles	0.01	1.3	2300	840
External floor	Exposed concrete floor	Reinforced concrete floor	0.1	2.3	2300	1000
		Concrete screed	0.05	1.35	2000	1000
Ceiling	The inverse of internal floor	Ceramic tiles	0.01	1.3	2300	840
		Concrete screed	0.05	1.35	2000	1000
		Reinforced concrete floor	0.1	2.3	2300	1000

from the present (IWEC) to the 2080s. The incremental percentage change for temperature from present to 2020s, 2050s, and 2080s is 3.6%, 3.9% and 5.4% respectively while the cumulative change by the year 2080s is 13.4%. The sensitivity analysis and optimisation process were run for the present climate (IWEC) and the future climate of the year 2080s. The objective of this study is to address how drastically these climate changes will alter the optimized solution and what determinant decisions the designer can make to ensure long-term efficient performance.

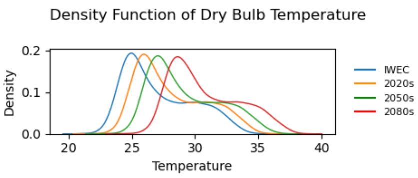


Figure 2: The probability density function of temperature from the present to the year 2080.

Sensitivity analysis

In the context of building performance simulation (BPA), sensitivity analysis is widely used to identify the most influential design parameters (the input) on the building performances (the output). The sampling and the analysis have been performed using the global sensitivity analysis method, namely the enhanced Morris Method or Elementary Effect (EE) method (Ruano et al., 2012). Morris's method can effectively measure the ranking of the effect even when the model is non-monotonic, which is the case for the energy and daylight model. In this study, 20 trajectories (k) and 4 levels were used and a total number of 240 samples were generated for each climate scenario. The number of samples (n) was obtained from equation 1, where D is the number of input parameters (i.e. 11) and k is the number of trajectories.

$$n = k(D + 1) \qquad (1)$$

All procedures to perform the Morris sampling and the Morris sensitivity analysis were run in Python 3.0 using the SALib module version 3.0.

The multi-objective optimisation

The multi-objective optimisation was performed using the Grasshopper plug-in Wallacei version 2.5. Wallacei employs the NSGA-II algorithm as the primary evolutionary algorithm. The algorithm sought to maximise UDIa and UR while minimising the rest of the objective functions. To find the optimal solution for the base case, the RO, RW, RD and RH were kept constant and were set the same as the base case. The height of the light shelf is 2.5m which is the lowest possible height clearance for a residential building according to Malaysian Uniform Building by Law (UBBL). Table 3 shows the minimum and maximum range of the 7 input parameters for the optimisation. The total number of design alternatives for the optimisation process was 2,606,175. For the setting of the optimisation process, the total population size was 5000 population with a generation size of 50 and a generation count of 100. The Crossover probability was set as 0.9, the mutation probability as 0.7 and the crossover and mutation distribution index as 20. With these settings, the simulation runtime took around 428 hours (17.8 days) for the present climate and 433 hours (18 days) for the future climate using AMD Ryzen 9 3900X 12-Core Processor with 64.0GB RAM.

Table 3: The input parameters for optimization

Parameters	Min	Max	Steps	Counts
SD	0.0m	5.0m	0.5m	11
GR	10%	90%	10%	9
GT	0.1	0.9	0.1	9
ELSD	0.0m	1.0m	0.25m	5
ILSD	0.0m	1.0m	0.25m	5
ELSA	-15°	45°	5°	13
ILSA	-15°	25°	5°	9
The total number of design alternatives:				2,606,175

Results

This section outlines the results of the sensitivity analysis and optimisation of the study. The first part of this section summarises the ranking and the influence of design parameters on daylight and energy performance through the Morris analysis. The second part of this section provides the main findings of the optimisation of the parameters by comparing the results with the base cases.

Sensitivity analysis results

The sensitivity analysis aimed to determine the highly influential parameters and their relationship to the output metrics. The sampling process conducted with the Morris method identified four values within each of the 11 parameters. Morris method uses the one-at-a-time method (OAT) to arrange the simulation run where each parameter was assigned one out of the four values and the subsequent run differed from the previous run for one of these values only. One of the key findings of the sensitivity analysis was illustrated in Figure 3. The figure gives an indication of the parameter's relationship with the outputs, based on the ratio $\sigma/\mu*$. σ is the standard deviation of differences in outputs due to input variation, which is also called the elementary effect. On the other hand, the $\mu*$ is the mean absolute value of the distribution. The relationship between the parameters and the outputs is represented by its position with three lines in the graph. If the parameters are positioned below the line $\sigma/\mu* = 0.1$, it can be considered to have an almost linear relationship with the outputs. If they appear below the line $\sigma/\mu* = 0.5$ and $\sigma/\mu* = 1$, then they are considered to have a monotonic and an almost-monotonic relationship respectively. On the other hand, if the parameters sit above the line $\sigma/\mu* = 1$, the parameters show a highly non-linear relationship with the output (Ruano et al., 2012). The figure also shows the ranking of the input parameters where the rankings are in order of most influential to least influential from right to left of the graph. The input parameters were depicted with different symbols. Blue-coloured symbols represent the results of the present climate, and red-coloured symbols represent the future climate.

Commented [A1]: Is this BPS?

For all output metrics, the rankings of the input parameters for present and future climate exhibit a similar pattern while it has a different variation for each metric. For UDIa, UDIs and UDIe, the most influential parameter is GT followed by RD and GR for both present and future climate. However, the least influential parameters for UDIa and UDIs are ELSA and ELSD while UDIe is least affected by ELSA and ILSA. For UR, the most influential input parameters are SD, RW and RD while RO shows the least influential parameters for this metric. The LTE's rankings behave similarly to the annual daylight metrics which it mostly affected by the variation in GT. But LTE is least affected by the variation in RO and ELSA. The results for CLE and SGE show that the RD is the most influential factor while the least influential factors are ILSA and ILSD. Additionally, room orientation (RO) shows a peculiar result where it is ranked mostly as not significant compared to the other factors. This is because the sun angle in tropical climates does not vary greatly throughout the year.

Figure 3 also gives an insight into the relationship between the input parameters and the output metrics. None of the parameters can be linearly correlated to any of the metrics. Most parameters for UDIa, UDIs and UDIe had a non-monotonic behaviour due to illuminance instances that do not fall within the specified range. For example, if the input parameter results in an illuminance value outside the range of 100 lux to 2000 lux for UDIa, the effect on the metric was a reduction in percentage rather than a corresponding increase. The behaviour of input parameters for LTE behaves similarly to those of annual daylight metrics where the lower-ranking parameters had a non-monotonic relation while the higher-ranking parameters had a monotonic relationship. On the other hand, the effect of the input parameters on UR was varied as depicted in the fourth graph of Figure 3. As for CLE and SGE, all parameters show a monotonic or almost-monotonic effect on the metrics, meaning that there was a corresponding increment and reduction in the resulting metrics, although not in a comparative manner.

Optimisation results

Two extreme cases of the base cases were simulated to analyse the impact of shaded and non-shaded rooms in present and future climates. As noted previously, the shading provision in the tropical climate would have a reciprocal effect towards daylighting and energy performance. The result from the optimisation is expected to find the trade-off between these two extreme cases. The two base cases were shaded and unshaded where it is addressed as BCs and BCus respectively from here onwards.

The optimisation results are presented in Figure 4 and Table 4. Figure 4 depicts the Pareto Front solutions for the present and future climate of the studied case. To better understand the relationship between daylight and energy output, each objective was mapped in a 3 x 4 metric where the x-axis represents the daylight-related metrics (i.e UDIa, UDIs, UDIe and UR) and the y-axis represents the energy-related metrics (i.e LTE, CLE and SGE). There were 50 Pareto Front potential solutions produced for each climate which were indicated by the blue circle and red triangle markers for the present and future climate respectively. The grey markers in Figure 4 (a), (e) and (i) indicate the solutions that do not meet the daylight threshold of the UDIa level of 50%. There are 28 out of 50 solutions that do not meet this requirement in the present climate. While in the future climate, 21 solutions failed to meet this requirement. There are 5 separate data points for each climate representing the BCs (aqua), BCus (magenta), the maximum daylight improvement (dark green), the maximum energy saving (yellow) and the proposed solution within this study (lime) (Figure 4). At these points, the maximum UDIa level for the present climate is 57.9% with 34.6% in UDIs and 0% in UDIe. The maximum level of uniformity ratio is 0.7. On the other hand, the minimum lighting EUI level is 11.6

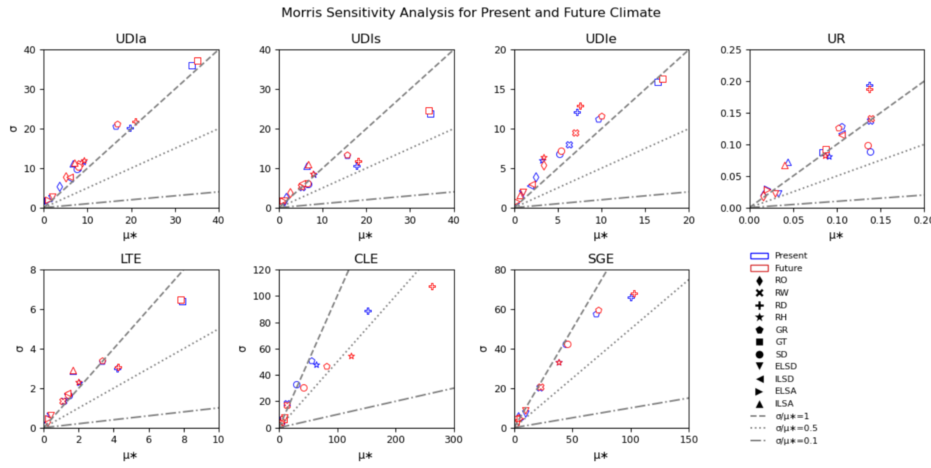


Figure 3: The result of Morris sensitivity analysis.

kWh/m^2 with 0 kWh/m^2 in cooling EUI and 18.1 kWh/m^2 in solar gain EUI. The maximum improvement in future climate is very similar to the present climate except for cooling and solar gain EUI (2.2 kWh/m^2 and 19.1 kWh/m^2 respectively). Table 4 also outlines the average percentage change of these maximum improvements compared to both base cases (BCs and BCus). Moreover, Figure 4 reveals the impact of future climate scenarios on daylight and thermal energy. The results of daylight-related metrics on LTE and SGE in the future climate (Figure 4 (a) to (d) and (i) to (l)) overlapped with the present climate which shows that its impact is minimal in the future climate. However, a stark difference can be seen in the Cooling EUI where in the future climate, the cooling EUI is relatively higher than the present climate. This trend further emphasizes the need to find an optimal trade-off between cooling energy and daylight in the future climate.

A further search was conducted to find the most feasible solution that ensures improvement in each fitness objective simultaneously. The data point in Figure 4 marked with lime-coloured markers named P7 for present

Table 4: The comparison of selected solution and maximum improvement to the base cases

Objectives	Present						Future					
	BCs	BCus	Max. Value[1]	**Change %[2]**	User Selection (P7)	**Change %[2]**	BCs	BCus	Max. Value[1]	**Change %[2]**	User selection (F49)	**Change %[2]**
UDIa	46.9	51.1	57.9	**18.4**	55.7	**13.4**	49.3	53.2	57.9	**13.1**	56.4	**10.2**
UDIs	53.1	45.4	34.6	**-29.3**	44.5	**-9.0**	50.7	43.3	34.5	**-26.1**	43.6	**-6.7**
UDIe	0.0	3.4	0.0	**-50.0**	0.0	**-50.0**	0.0	3.5	0.0	**-50.0**	0.0	**-49.6**
UR	0.3	0.3	0.7	**133.3**	0.7	**124.7**	0.3	0.3	0.7	**133.3**	0.7	**126.6**
LTE	15.0	13.2	11.6	**-17.4**	13.1	**-6.5**	14.7	13.0	11.6	**-15.9**	13.0	**-5.6**
CLE	0.0	0.3	0.0	**-50.0**	0.0	**-50.0**	1.3	24.1	2.2	**-10.8**	2.5	**-0.5**
SGE	11.7	37.2	18.1	**1.7**	18.1	**1.8**	11.8	38.8	19.1	**5.5**	19.9	**10.0**

[1] Result of maximum improvement from all Pareto Front solutions.
[2] The change is calculated as an average percentage change of the new solution to both base cases (BCs and BCus)

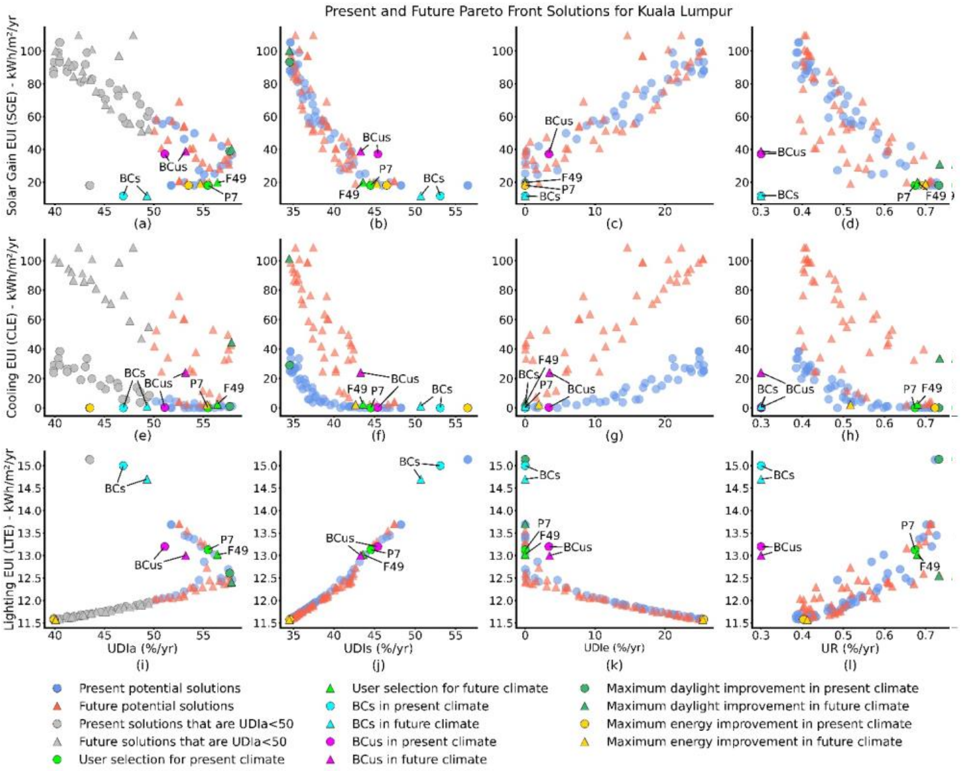
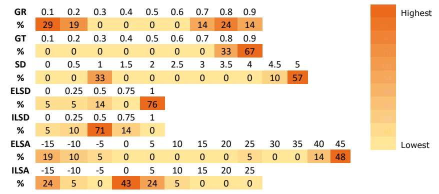


Figure 4: The result of Pareto Front solutions for present and future climate

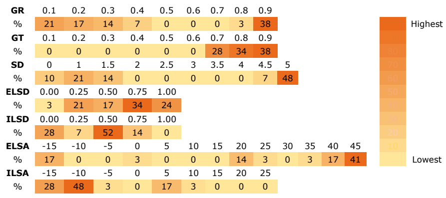
climate and F49 for future climate were selected as the most feasible solution. The selection was based on a positive increment in daylight level and decrement energy usage compared to both base cases. As outlined in Table 4, UDIa of user-selected solutions observed an average increment of 13.4% in the present climate and 10.2% in the future climate when compared to both base cases. Correspondingly, the UDIs and UDIe showed a reduction of 9% and 50% respectively in the present climate while in the future climate, it was reduced by 6.7% and 49.6% respectively. There is a large improvement in terms of the uniformity ratio where it has increased by 124.7% in the present climate and 126.6% in the future climate. Accordingly, due to the improvement of daylight level, the lighting EUI showed an average reduction of 6.5% and 5.8% in the present and future climate respectively. The cooling EUI usage also observed an average decrease of 50% and 0.5% in each climate. The introduction of the light shelf in the room caused the solar gain EUI to increase by 1.8% and 10% in the present and future climate respectively. If we observed the absolute value of this increase, the selected solution performed better than the unshaded base case (BCus) which means that the selected solution found a trade-off between shaded and unshaded rooms.

Figure 5 and Table 5 shows the overall genomic analysis of acceptable solutions for the present climate and future climate. Figure 5 outlines the percentage of occurrence of a specific genome (input parameters) in the optimal solutions. The darker the colour, the higher the percentage of the genome that appeared in the optimal solution. Thus, it indicates the importance of the genome as the effective solution for the studied climate. This section will compare to the genomic analysis of the present climate to the future climate to examine how the optimal solutions change against varying climate scenarios. For the GR parameter, the results of the present climate revealed a change in behaviour to the future climate. The effective window-to-wall ratio for the present climate appeared frequently with the lowest ratio (0.1) while in the future climate, the highest ratio of glazing was preferred (0.9). In the case of the GT parameter, the most desirable genome for the present and future climate was the same (0.9), however, lower GT options such as 0.7 and 0.8 become equally desirable in the future climate. This is likely due to the increased trend of temperature in the future climate. As for the depth of the overhang, the longest shade is considered the most effective solution for both climates. The preferred genome for ELSD also observed a decrease from 1.00m in the present climate to 0.75m in the future climate. However, the ILSD of the future climate remained the same as in the present climate. The highest genomic occurrence for external light shelf inclination also remained the same as the present climate, which is 45^0. The inclination angle of -10^0 for the internal light shelf showed the highest occurrence in the optimal solutions for the future climate whereas, 0^0 was selected as the most effective solution in the present climate.

In Table 5, the introduction of a light shelf caused the glazing ratio of the selected solution to reduce from 0.3 (BCs and BCus) to 0.1 in both climates. On the other hand, the selected GT for both climates was increased from 0.6 to 0.9. In the case of the SD parameter, the depth of the selected solution was reduced by 1.0m for both climates. In terms of light shelf parameters, the preferred genomes for the selected solutions were within the range as discussed previously.



(a)



(b)

Figure 4: Genomic analysis of acceptable solutions for the present climate (a) and future climate (b).

Table 5: The genomic result of the selected solutions in the present climate and future climate.

Cases	GR (%)	GT	SD (m)	ELSD (m)	ILSD (m)	ELSA (deg)	ILSA (deg)
P7	0.1	0.9	5.0	1.00	0.50	45	-15
F49	0.1	0.9	5.0	0.75	0.50	45	-10

Discussion and Conclusion

This paper investigated the use of global sensitivity analysis with a multi-objective optimisation framework to achieve a high-performance façade design for a residential building. The approach was applied to an intermediate unit of terrace housing in Kuala Lumpur, which represents a hot and humid climate in Malaysia. Two varying climate scenarios that represent present and future climates were also investigated in the study. The Morris sensitivity analysis method was applied to determine the influential input parameters on 7 selected output metrics. After the influential parameters have been determined, the optimal set of daylight and energy-saving solution were identified through the optimisation process.

The deduction from sensitivity analysis results demonstrates that in a hot and humid climate, GT was consistently ranked as the most influential parameter for annual daylight metrics and lighting EUI. For daylight uniformity, RW, RD and SD showed the highest and equivalent importance to the output. While for thermal energy metrics such as cooling and solar gain EUI, RD is ranked as the most important parameter. In terms of light shelf parameters, it was observed that the internal light shelf parameters were more sensitive to daylight-related metrics while the external light shelf parameters were more sensitive to the thermal energy metrics.

The assumption from the solutions of the optimisation process reveals a trade-off relationship between daylight and thermal energy performance. In general, the daylight performance of the selected solution observed an improvement while thermal energy performance showed a balanced between two extreme base cases. Furthermore, the presence of a light shelf has greatly improved the performance of daylight uniformity. The optimisation process also explains the changing optimal solution from present to future climate, especially to the parameters that were highly sensitive according to the sensitivity analysis results.

In conclusion, it became evident that the use of sensitivity analysis along with multi-objective optimisation can support solving multi objectives design problems. The relationship between conflicting objectives can be thoroughly analysed and the best trade-off solution can be determined. For future work, many other sampling schemes and sensitivity techniques could be explored to assess the most suitable techniques for the study. This research is part of a larger research to explore the use of meta-model techniques to improve the efficiency of the computation time of the optimisation process. The optimisation process for both climate scenarios consumed nearly 861 hours on a desktop computer with AMD Ryzen 9 3900X 12-Core Processor with 64.0GB RAM. This can be seriously unrealistic to be implemented in an actual project, especially when considering more complex design problems. Besides, the work should be extended to another performance metric such as thermal comfort and the results should be validated by comparing the outputs to monitored data.

Acknowledgement

This study was developed as part of a PhD dissertation at the Welsh School of Architecture, Cardiff University, with combined funding from the Ministry of Higher Education Malaysia (MOHE) and the Universiti Tun Hussein Onn (UTHM) Malaysia.

Nomenclature

GR - Window-to-wall ratio or glazing ratio (%)
GT - Glazing transmittance
SD - Shade depth (m)
ELSD - Depth of external light shelf (m)
ILSD - Depth of internal light shelf (m)
ELSA - Angle of the external light shelf (^{0})
ILSA - Angle of the internal light shelf (^{0})
UDIa - Acceptable useful daylight illuminance
UDIs - Supplementary useful daylight illuminance
UDIe - Excessive useful daylight illuminance
UR - Daylight uniformity ratio
LTE - Annual lighting energy use intensity (kWh/m^2)
CLE - Annual cooling energy use intensity (kWh/m^2)
SGE - Annual solar gain energy use intensity (kWh/m^2)

References

Andrea, S., Marco, R., Terry, A., Francesca, C., Jessica, C., Debora, G., Michaela, S., & Stefano, T. (2008). *Global Sensitivity Analysis. The Primer*. John Wiley & Sons Ltd.

Bahdad, A. A. S., Fadzil, S. F. S., Onubi, H. O., & BenLasod, S. A. (2021). Sensitivity analysis linked to multi-objective optimization for adjustments of light-shelves designs parameters in response to visual comfort and thermal energy performance. *Journal of Building Engineering*, *44*.

Department of Standards Malaysia. (2017). *Malaysian Standard: Energy Efficiency and Use of Renewable Energy for Residential Building (MS 2680:2017)*.

Jentsch, M. F., James, P. A. B., Bourikas, L., & Bahaj, A. S. (2013). Transforming existing weather data for worldwide locations to enable energy and building performance simulation under future climates. *Renewable Energy*, *55*, 514–524.

Mohamed, A., Homod, R. Z., Shareef, H., Ahmed, M. S., & Khalid, K. (2017). Awareness on energy management in residential buildings: A case study in Kajang and Putrajaya. In *Article in Journal of Engineering Science and Technology* (Vol. 12, Issue 5).

Nabil, A., & Mardaljevic, J. (2005). Useful daylight illuminance: a new paradigm for assessing daylight in buildings. *Lighting Research & Technology*, *37*(1), 41–57.

Nik Ramzi Shah, N. F. E., & Mohd. Rasdi, M. T. (2017). *Rumah Teres dan Keserasian Budaya Masyarakat Malaysia* (1st ed.). Dewan Bahasa dan Pustaka.

Pang, Z., O'Neill, Z., Li, Y., & Niu, F. (2020). The role of sensitivity analysis in the building performance analysis: A critical review. In *Energy and Buildings* (Vol. 209). Elsevier Ltd.

Ruano, M. V., Ribes, J., Seco, A., & Ferrer, J. (2012). An improved sampling strategy based on trajectory design for application of the Morris method to systems with many input factors. *Environmental Modelling and Software*, *37*, 103–109.

Shahbazi, Y., Heydari, M., & Haghparast, F. (2019). An early-stage design optimization for office buildings' façade providing high-energy performance and daylight. *Indoor and Built Environment*, *28*(10), 1350–1367.

Yu, F., Wennersten, R., & Leng, J. (2020). A state-of-art review on concepts, criteria, methods and factors for reaching 'thermal-daylighting balance.' In *Building and Environment* (Vol. 186). Elsevier Ltd.

Zani, A., Andaloro, M., Deblasio, L., Ruttico, P., & Mainini, A. G. (2017). Computational Design and Parametric Optimization Approach with Genetic Algorithms of an Innovative Concrete Shading Device System. *Procedia Engineering*, *180*, 1473–1483.

Commented [A2]: This looks wrong